A Probabilistic Modeling Based Forecasting Approach To Predict Future Photovoltaic Power Generation

Subrat Kumar, Santosh Kumar

Department of Electrical & Electronics Engineering, Millennium Institute of Technology & Science, Bhopal (M.P)

Abstract: The ability to accurately forecast power generation from renewable sources is nowadays recognised as a fundamental skill to improve the operation of power systems. Despite the general interest of the power community in this topic, it is not always simple to compare different forecasting methodologies, and infer the impact of single components in providing accurate predictions. In recent years, global energy demand has increased dramatically. Several factors have contributed to this rise: the growth of the world population, the industrialization of developing countries, and the worldwide process of urbanization. The exploitation of the main conventional sources, fossil fuels, has proven to be detrimental for the environment and, therefore, alternative Renewable Energy Sources (RESs) have gained wide interest.In this context, high PV penetration provides many environmental and economic benefits, but the stochastic behavior of the solar power may also introduce technical issues (e.g., generation schedule, operating reserve, market regulation, etc.) without robust and precise forecast. A reliable forecast is the key for several smart-grid applications, such as optimal dispatch, active demand response, grid regulation, and intelligent energy management.In this work we extensively compare simple forecasting methodologies with more sophisticated ones over photovoltaic plants of different size and technology over a whole year. Also, also try to evaluate the impact of weather conditions and weather forecasts on the prediction of PV power generation.

Keywords - PV plants, Machine Learning algorithms, power generation forecasts.

I. INTRODUCTION

High penetration levels of Distributed Energy Resources (DERs), typically based on renewable generation, introduce several challenges in power system operation, due to the intrinsic intermittent and uncertain nature of such DERs. In this context, it is fundamental to develop the ability to accurately forecast energy production from renewable sources, like solar photovoltaic (PV), wind power and river hydro, to obtain short- and mid-term forecasts. Accurate forecasts provide a number of significant benefits, namely:

• Dispatchability: secure power frameworks' day by day activity mostly depends upon day-ahead dispatches of intensity plants [1]. Appropriately, important day-ahead plans can be performed just if exact day-ahead expectations of intensity age from sustainable sources, along with dependable forecasts of the day-ahead burden utilization estimates are accessible;

• Efficiency: as output power changes from discontinuous sources may cause recurrence and voltage variances in the framework, a few nations have presented punishments for power generators that neglect to precisely foresee their capacity age for the following day; in this manner, some vitality makers like to think little of their day-ahead power age estimates to stay away from to acquire in punishments in the following day. Such actuated preservationist practices are unmistakably not proficient;

• Monitoring: bungles between power conjectures and the really created power might be likewise utilized by vitality makers to screen the plant activity, to assess the common debasement of the proficiency of the plant because of the maturing of certain parts or for early identification of early blames. For the past reasons, the subject of sustainable power source guaging has been likewise object of some ongoing reading material like [5] and [6] that give outlines of the best in class of the latest innovations and utilizations of sustainable power source forecasting. In this specific situation, the target of this work is to contrast various approaches with anticipate day-ahead hourly power age from PV power plants.

II. LITERATURE REVIEW

In this paper an overview of the previously proposed papers is given this will ultimately help to examine the disadvantages, advantages as well as the proposed work.

In this paper [22] creator presented Photovoltaic (PV) power age is described by noteworthy fluctuation. Exact PV conjectures are an essential to safely and monetarily working power systems, particularly on account of enormous scope infiltration. In this paper, we propose a probabilistic spatio-worldly model for the PV power creation that abuses creation data from neighboring plants. The model gives the total future likelihood thickness capacity of PV creation for extremely momentary skylines (0-6 hours). The strategy depends on quantile relapse and a L1 punishment procedure for programmed choice of the information factors. The proposed displaying chain is basic, making the model quick and adaptable to coordinate on-line application. The presentation of the proposed approach is assessed utilizing a certifiable experiment, with a high number of geologically disseminated PV establishments and by examination with cutting edge probabilistic strategies.

In this paper [23] creator proposed Integration of high volume (high infiltration) of photovoltaic (PV) age with power frameworks therefore prompts some specialized difficulties that are principally because of the irregular idea of sun based vitality, the volume of information associated with the shrewd network design, and the effect power electronic-based brilliant inverters. These difficulties incorporate converse force flow, voltage fluctuations, power quality issues, dynamic strength, huge information difficulties and others. This paper examines the current difficulties with the flow level of PV infiltration and investigates the difficulties with high PV entrance in future situations, for example, keen urban areas, transactive vitality, multiplication of module half breed electric vehicles (PHEVs), conceivable obscuration occasions, enormous information issues and ecological effects. Inside the setting of these future situations, this paper checked on the current arrangements and gives bits of knowledge to new and future arrangements that could be investigated to at last location these issues and improve the brilliant matrix's security, unwavering quality and flexibility.

In this paper [24] creator proposed Solar vitality is assuming an essential job in repaying the electrical vitality as there is deficit in this vitality because of more interest and decay patterns of ordinary wellspring of energies depletion of powers like coal, oil, regular gases and steady of natural and climatic changes to adapt up this photovoltaic establishment is being done in an electrical framework to redress and improve the vitality. A photovoltaic establishment in an electrical framework is produced using the get together of different photovoltaic units that utilizes sun oriented vitality to create the power in a less expensive manner from sun power. Till now the utilization and extent of sunlight based vitality is restricted and has not reached upto masses Moreover the productivity of the framework is additionally low because of which the output isn't adequate when contrasted with contribution as in some introduced instance of sun powered board it has been seen that proficiency isn't more that 27%. To make it flexible and progressively valuable for the majority more up to date patterns and advancements will help. These have talked about in this paper.

In this paper [25] creator proposed Solar force's inconstancy makes overseeing power framework arranging and activity troublesome. Encouraging an elevated level of coordination of sun based force assets into a matrix requires keeping up the major force framework with the goal that it is steady when interconnected. Exact and solid anticipating assists with keeping up the framework securely given huge scope sun oriented force assets; this paper consequently proposes a probabilistic guaging way to deal with sunlight based assets utilizing the R insights program, applying a half breed model that considers spatio-transient idiosyncrasies. Data on how the climate changes at locales of intrigue is frequently inaccessible, so we utilize a spatial demonstrating system called kriging to assess exact information at the sunlight based force plants. The kriging technique executes introduction with topographical property information. In this paper, we perform day-ahead conjectures of sun based force dependent on the likelihood in one-hour spans by utilizing a Naïve Bayes Classifier model, which is a grouping calculation. We expand determining by considering the general information dissemination and applying the Gaussian likelihood dispersion. To approve the proposed mixture estimating model, we play out a correlation of the proposed model with a steadiness model utilizing the standardized mean total mistake (NMAE). Moreover, we utilize exact information from South Korea's meteorological towers (MET) to interject climate factors at focal points.

In this paper [26] creator proposed Photovoltaic frameworks have gotten a significant wellspring of sustainable power source age. Since sunlight based force age is inherently profoundly subject to climate variances, anticipating power age utilizing climate data has a few monetary advantages, including dependable activity arranging and proactive force exchanging. This examination manufactures a model that predicts the measures of sunlight based force age utilizing climate data gave by climate organizations. This examination proposes a two-advance demonstrating process that associates unannounced climate factors with reported climate estimates. The exact outcomes show that this methodology improves a base methodology by wide edges, paying little heed to sorts of applied AI calculations. The outcomes additionally show that the arbitrary backwoods relapse calculation plays out the best for this issue, accomplishing a R-squared estimation of 70.5% in the test information. The transitional demonstrating process makes four factors, which are positioned with high significance in the post-examination. The built model performs practical one-day ahead expectations.

III. PERFORMANCE OF PHOTOVOLTAIC SYSTEM

Uncertainties in revenue over time relate mostly to the evaluation of the solar resource and to the performance of the system itself. In the best of cases, uncertainties are typically 4% for year-to-year climate variability, 5% for solar resource estimation (in a horizontal plane), 3% for estimation of irradiation in the plane of the array, 3% for power rating of modules, 2% for losses due to dirt and soiling, 1.5% for losses due to snow, and 5% for other sources of error. Identifying and reacting to manageable losses is critical for revenue and O&M efficiency. Monitoring of array performance may be part of contractual agreements between the array owner, the builder, and the utility purchasing the energy produced. A method to create "synthetic days" using readily available weather data and verification using the Open Solar Outdoors Test Field make it possible to predict photovoltaic systems performance with high degrees of accuracy.[28]

IV. PROBLEM DEFINITION

1. Since predictive relationships are complex and difficult to grasp, this study tests several machine learning algorithms, such as multi-layer perceptron, k-NN, ANN, and SVM, which are suitable for the structure of the data and the problem. Before applying the machine learning algorithms, proper scaling is performed.
2. The focus will be placed in benchmarking ML and time series techniques. Many of the above models are generic and therefore do most of them have a wide range of different model set-ups. The aim is to give a general overview of the relative performance of the methods rather than investigating a specific model in depth.
3. Supply planning on renewable energy operations, such as sunlight, wind, tides, and geothermal energy, involves a unique (unique class) class of prediction problem because these natural energy sources are intermittent and uncontrollable, due to fluctuating weather conditions.
4. Though a few variables in weather observation were missing in weather forecasts, this study aimed to fully exploit weather information for building prediction process. That is, the weather observation variables were predicted using weather forecast variables.
5. This study validates that the process of latent structure identification improves the solar power generation problem and aids PV plant operations. Furthermore, other renewable energy operations, such as wind, tide, and geothermal power production, can also be benefitted from the proposed approach. More generally, it can also be applied to other fields that require predicting future weather conditions.

V. PROPOSED METHODOLOGY

In this section an explanation of the proposed algorithm is given-

Collection of yearly meteorological data from National Renewable Energy Laboratory (NREL) of hourly resolution as-The TMY data sets hold hourly values of solar radiation and meteorological elements for a 1- year period. Their intended use is for computer simulations of solar energy conversion systems and building systems to facilitate performance comparisons of different system types, configurations, and locations in the States. Because they represent typical rather than extreme conditions, they are not suited for designing systems to meet the worst-case conditions occurring at a location.

Below is the flowchart of the proposed algorithm is shown in 1-

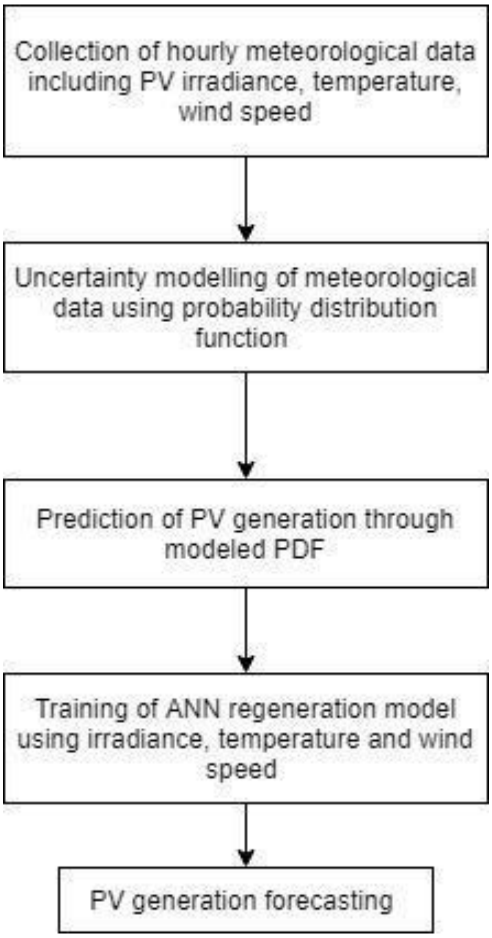

Figure 1: Flowchart of proposed algorithm.

Modeling the uncertainty in collected data using probability distribution function (PDF)- a probability distribution function, or density of a continuous random variable, is a function whose value at any given sample in the sample space can be interpreted as providing a relative likelihood that the value of the random variable would equal that sample.

Generation prediction through modeled PDF-the prediction of the generation will be done on the basis of probability distribution function

Artificial Neural Network Regression Model-ANNs are a wide class of logical structures freely inspired by the human brain. They are vastly used in PV forecasting. This is testified by the fact that almost 25% of the papers proposed in the literature on this topic are ANN-based. The architecture adopted in this article is the Multi-Layer Perceptron (MLP). Figure 4.1 provides the general structure of an MLP.

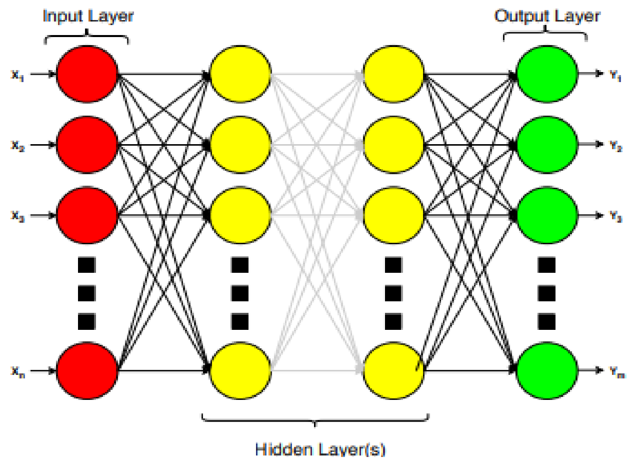

Figure 2: A multi-layer perceptron.

Its architecture consists of three parts: input layer, at least one hidden layer and output layer. Each layer receives the inputs from the preceding layer and, by means of weighting, translation, and a nonlinear transformation, passes them to the next layer. The input layer processes the original input vector, while the output layer passes the processed values to the user. In this work an ensemble technique has been exploited within the ANN approach.

PV generation forecasting-at last the generation of the PV forecasting is done.

VI. SIMULATION SETUP

For the Experimental simulation, the Classification stage has been validated using MATLAB simulation. The MATLAB code was developed using the MATLAB m-file editor toolbox. The test results and performance of the algorithm are shown in the following below sections.

PARAMETERS USED

The model is able to analyze the variation of PV parameters such as the ideality factor ,Series resistance, thermal voltage and Band gap energy of the PV module with temperature as well as time. Finally a novel intelligent method based technology is proposed.

Irradiance=the flux of radiant energy per unit area (normal to the direction of flow of radiant energy through a medium).

RESULT ANALYSIS

In this section the outputs obtained at different stages is given-

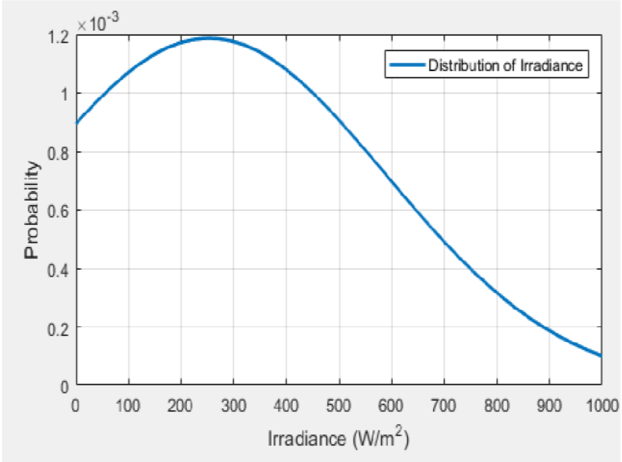

Figure 3: Probability distribution of irradiance over a period of one year.

in the above figure 3 the graphical representation of the irradiance W/m^2 to the probability is shown on to that the values of the probability is taken from 0 to 1.2 *10^{-3} and the value of irradiance is taken from 0 to 1000. the value of the graph is at the peak at 1.2 in between 200 to 300 irradiance W/m^2

Table1 Comparative analysis in between parameters used.

Parameters	1-1000
Irradiance W/m^2	1.2
temperature (deg)	0.05
wind speed (m/s)	0.3

in the above table 1 the comparative analysis of the parameters like-Irradiance W/m^2 temperature (deg), wind speed (m/s). the values obtained are also shown in the table which then put onto the graphical representation.

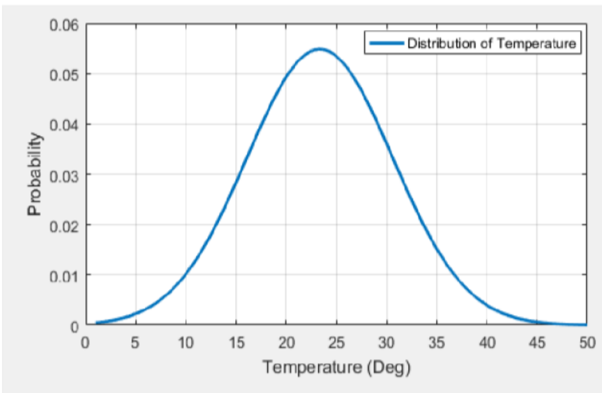

Figure 4: Probability distribution of temperature over a period of one year

in the above figure 4 the graphical representation of the temperature (deg)to the probability is shown on to that the values of the probability is taken from 0 to 0.06 and the value of temperature is taken from 0 to 50. the value of the graph is at the peak at 0.05 in between 20 to 30 deg.

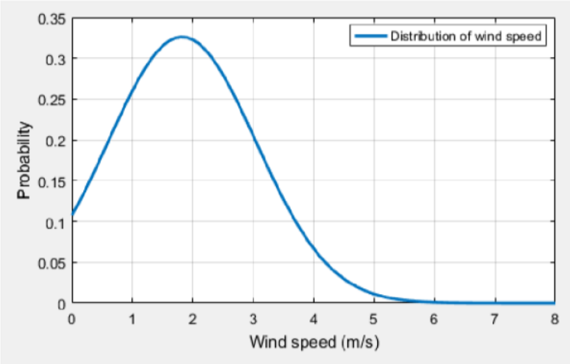

Figure 5: Probability distribution of Wind speed over a period of one year

in the above figure 5 the graphical representation of the wind speed (m/s)to the probability is shown on to that the values of the probability is taken from 0 to 0.35 and the value of wind speed is taken from 0 to 8 the value of the graph is at the peak at 0.3 in between 1 to 3 in m/s.

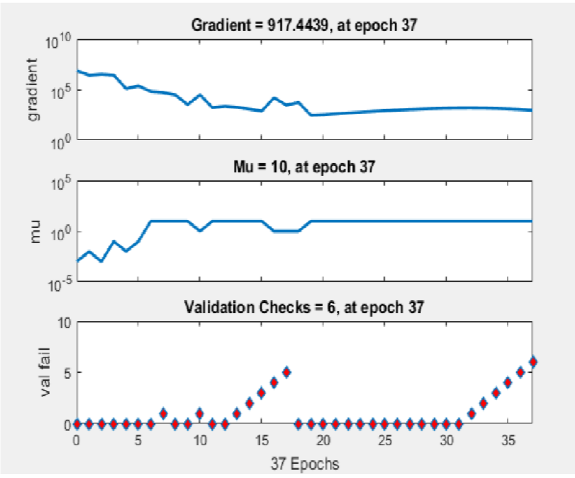

Figure 6: Performance of ANN regression model

in the above figure 6 the performance of ANN regression model is shown onto that the values of parameters like-gradient-917.4439 at epoch 37, value of mu-10 at epoch 37, val fail checks-6 at epoch 37 is shown.

Table 2 Comparative analysis in between parameters used.

Parameters	1-1000
Gradient	917.4439
mu	10
val fail	6

in the above table 2 the comparative analysis of the parameters like-gradient, mu, val fail. the values obtained are also shown in the table which then put onto the graphical representation.

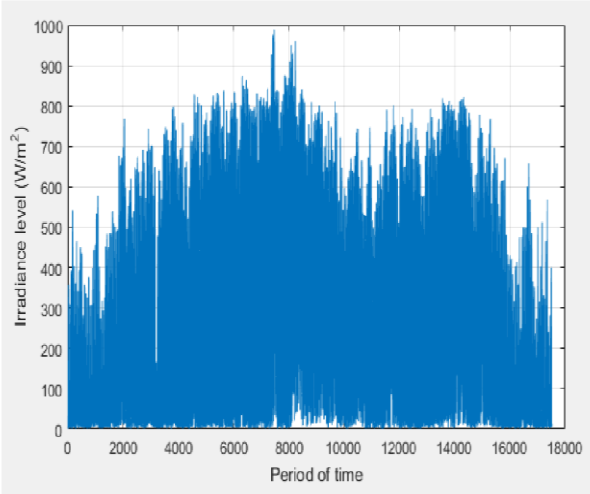

Figure 7: Yearly forecasted data of Irradiance (W/m^2)

in the above graph 7 the variation in values is shown on which the value range of irradiance ia taken from 0 to 1000 and time period is taken from 0 to 18000 in m/s.

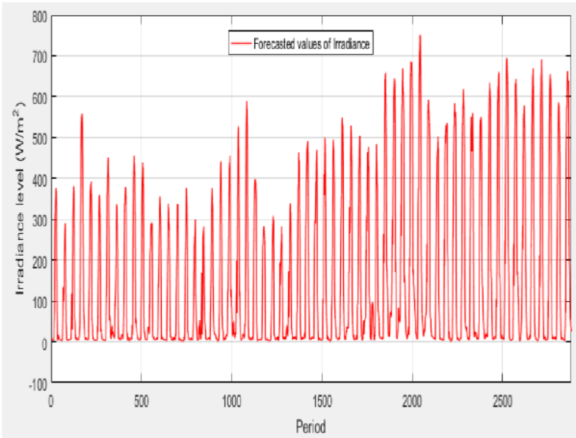

Figure 8: Monthly forecasted data of Irradiance (W/m^2)

in the above figure 8 the graphical representation of the monthl forecasted data of Irradiance (W/m^2) is shown.

VII. CONCLUSION & FUTURE WORK

This study proposes a two-step approach to solar power generation prediction to fully exploit the information contained in the weather data. Specifically, the predicted values for auxiliary variables contribute greatly to enhancing prediction performance. Skewed errors result in lower overall accuracy, especially for the power plant located in areas of unpredictable weather.To aid actual operations, it would be meaningful in future studies, especially for areas with low weather predictability, to present confidence intervals of the predicted value, as well as the predicted values themselves. This work exemplifies a practical application of feature extraction such that latent variables, relevant but delayed weather data in this study, are identified prior to the main modeling. This study validates that the process of latent structure identification improves the solar power generation problem and aids PV plant operations. Furthermore, other renewable energy operations, such as wind, tide, and geothermal power production, can also be benefitted from the proposed approach. More generally, it can also be applied to other fields that require predicting future weather conditions.

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